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Fuel Demand, Spatial Competition, and Local Market Structure: Evidence from Gasohol Retailing in Lima and Callao †

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Abstract

This study examines the relationship between real retail prices and sales of 90- and 95-octane gasohol in Metropolitan Lima and Callao from March 2020 to December 2022. Using monthly district-level data from Osinergmin, the analysis estimates log-log specifications with district and month fixed effects, complemented by sensitivity checks and exploratory instrumental-variable exercises based on fuel reference prices and local spatial competition. In the full sample, a 1% higher real price is associated with approximately 1.50% lower sales of 90-octane gasohol and 2.20% lower sales of 95-octane gasohol. For 2021–2022, the corresponding estimates are -2.46 and -3.17. The negative associations persist after allowing for differential socioeconomic trajectories across districts. The analysis is complemented by instrumental-variable exercises. The findings document local price–sales relationships during a period shaped by the COVID-19 pandemic and fuel-policy interventions.(*JEL*: H23, L11, Q41, R41)

Keywords: price elasticity of demand; gasohol; fuel market; Metropolitan Lima and Callao; spatial competition; market concentration; fixed effects; instrumental variables; Osinergmin; Selective Consumption Tax.

1 Introduction

In March 2006, Law No. 28694 (Gobierno del Perú, 2006) introduced the Fuel Harmfulness Index (*Índice de Nocividad de Combustibles*, INC) as a criterion for assigning the Selective Consumption Tax (*Impuesto Selectivo al Consumo*, ISC) to fuels, so that fuels considered more polluting would be taxed more heavily. The purpose of this rule was to promote a reduction in the consumption of polluting fuels and to encourage the adoption of alternatives more compatible with economic and environmental objectives. However, the drafting and publication of this law were not accompanied by an explicit analysis of demand elasticity, making it impossible to know *a priori* the expected impact of the policy on the quantity demanded in the local market.

To the best of the author's knowledge, no specific *ex post* analysis has been identified for this market. This paper therefore seeks to answer the following question: what is the price elasticity of demand in one of the markets affected by this regulation, namely the market for vehicular gasohol consumption in Metropolitan Lima and Callao (LMC)?

The analysis focuses on this product because vehicular gasohol consumption is a relevant source of pollutant emissions in LMC. In particular, this fuel, together with gasoline, accounts for 87% of the carbon monoxide (CO) emitted by mobile sources (Ministerio del Ambiente, 2021). The study also focuses exclusively on LMC because this area concentrates 65.9% of the national vehicle fleet (Ministerio de Transportes y Comunicaciones, 2020); it is classified as a Priority Attention Zone (*Zona de Atención Prioritaria*, ZAP) for air-quality management because the economic, vehicular, and urban activities carried out there generate a special impact on air quality (Gobierno del Perú, 2001); and the available information is more frequent, complete, and detailed than for other departments of Peru.

The analysis focuses on 90- and 95-octane gasohols because, jointly, they represent a substantive share of gasohol demand in Metropolitan Lima and Callao (Ministerio del Ambiente, 2021). This confirms their relevance within the local market and allows the study to work with more frequent and consistent price reports. The sample covers the period from March 2020 to December 2022 due to limitations in the availability of comparable data for earlier periods. However, this time frame also imposes an important restriction, because the beginning of the period coincides with mobility restrictions and economic disruptions associated with the COVID-19 pandemic. The results should therefore be interpreted as corresponding to an exceptional context.

The sample ends in December 2022 because, beginning in January 2023, a reform in the commercial classification of fuels came into effect. Under this reform, service stations stopped offering gasoline differentiated by specific octane levels such as 90 and 95 and began selling mainly two categories: regular and premium (Ministerio de Energía y Minas, 2022). The regular category grouped the 84- and 90-octane fuels, while the premium category grouped the 95-, 97-, and 98-octane fuels. Extending the database beyond 2022 would therefore require combining products defined under different classifications, introducing a measurement break in the price and quantity series.

To answer the research question, the paper uses data from the Supervisory Agency for Investment in Energy and Mining (Osinergmin) on the quantities and prices of gasohol

sold in LMC between March 2020 and December 2022. Because these data correspond to the market equilibrium resulting from the interaction of supply and demand forces, an ordinary least squares estimation may produce biased results. For this reason, the paper presents as its main specification a log-log model with district and month fixed effects, and complements the analysis with instrumental-variable exercises as a methodological diagnostic of possible price endogeneity.

Specifically, the extension uses an instrumental-variable strategy based on heterogeneous exposure to fuel cost shocks. The strategy is inspired by the logic of a Bartik instrument, widely used in empirical applications related to labor markets (Bertrand et al., 2015; Jaeger et al., 2018; Goldsmith-Pinkham et al., 2020; Fitchett and Wesselbaum, 2022), insofar as it exploits local differences in exposure to common shocks.

This study contributes to the literature in two ways. First, it provides empirical evidence to evaluate an existing policy whose implementation was not accompanied by explicit estimates of demand elasticity. Indeed, the economic analysis included in the documentation of the regulation consists of only eight lines, mainly devoted to describing potential enforcement costs and environmental benefits, without offering a calculation or quantitative estimate of the expected effect on consumption (Gobierno del Perú, 2004). Second, the paper proposes an instrumental-variable application to evaluate the possibility of isolating exogenous price variation in the Peruvian fuel market. This methodological contribution should be interpreted with caution, because its validity depends on the explicit discussion of the instrument's relevance and exogeneity.

The main estimates suggest a negative relationship between real prices and the quantity demanded of gasohol in LMC. In the full sample, the estimated elasticity is -1.50 for 90-octane gasohol and -2.20 for 95-octane gasohol. When the analysis is restricted to the 2021-2022 period, the estimated elasticities become larger in magnitude: -2.46 for 90-octane gasohol and -3.17 for 95-octane gasohol. These results suggest that demand responds to price, especially when distinguishing between fuel types and when excluding the period most affected by the initial mobility shock associated with COVID-19.

The results are in line with Liddle and Huntington (2020), who use panel data to estimate elasticities for 113 countries and conclude that developed countries tend to have more elastic gasoline demand than developing countries. One explanation proposed by the authors is that developed countries have better public transportation systems, which function as more effective substitutes when gasoline prices increase. Under that logic, LMC, whose public transportation system presents important deficiencies (TomTom, 2019; Barr Rosso, 2020), would be expected to display relatively less elastic demand.

However, this paper argues that, given the characteristics of LMC's transportation system, part of private vehicle use may be substitutable by other modes of transportation, even if these are not perfect substitutes. This possibility could help explain the high estimated sensitivity of gasohol demand to price. The results section discusses the rationale for this hypothesis and the sensitivity of the estimates in greater detail.

The remainder of the paper is organized as follows. Section 2 provides background on the gasohol market in Peru and in Metropolitan Lima and Callao. Section 3 reviews the re-

lated literature on fuel demand elasticity and instrumental variables. Section 4 describes the data. Section 5 presents the empirical strategy. Section 6 reports and discusses the results. Section 7 concludes.

2 Background

In recent years, the Peruvian gasoline market has undergone several changes. The most important has been the transition from gasoline consumption to gasohol, a fuel composed of 7.8% fuel alcohol and 92.2% gasoline of a given octane level. This measure was implemented in 2010 after the publication of Supreme Decree No. 091-2009-EM (Gobierno del Perú, 2009), which justified the decision on the grounds that this fuel generated less pollution and that lower price variation would result from domestic ethanol production. Currently, Loreto and Madre de Dios are the only departments exempt from complying with this rule, because raising the price of the product is considered unnecessary in regions where transportation difficulties already lead to higher prices.

Although part of the justification rests on the assumption that selling gasohol instead of gasoline would reduce the sensitivity of its price to factors external to the local market, gasohol still exhibits a high degree of volatility and remains sensitive to movements in the international fuel market, as discussed in Section 5.

A central element for interpreting the period of analysis is that it begins during the mobility restrictions and economic disruptions associated with the COVID-19 pandemic. From March 2020 onward, fuel demand may have been affected not only by price variation, but also by restrictions on movement, changes in labor activity, reduced commuting, remote work, and changes in consumption patterns. Moreover, the recovery of mobility and economic activity was not necessarily homogeneous across districts, since it may have depended on differences in income, productive structure, urban density, and access to alternative modes of transportation. The 2020-2022 period should therefore be understood as exceptional.

Figure 1 shows the monthly evolution of demand and real price indices for 90- and 95-octane gasohols. The initial drop in demand during 2020 illustrates the magnitude of the pandemic-related shock, while the subsequent recovery allows us to observe a market less dominated by the initial mobility restrictions. This descriptive evidence reinforces the decision to interpret the results for the full period with caution and to present alternative estimates for 2021-2022.

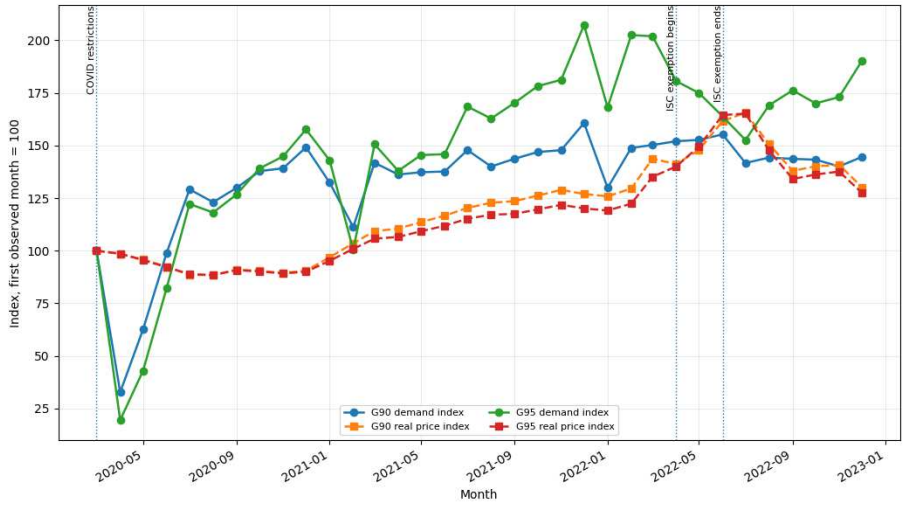
Another important element is the Fuel Price Stabilization Fund (*Fondo para la Estabilización de Precios de los Combustibles*, FEPC), created in 2004 to reduce the impact of international crude-oil price volatility on Peruvian consumers. The fund defines a price band such that, if the selling price is below the lower bound, the FEPC requires suppliers to raise it to that level and stores the excess gain; if prices are above the upper bound, the FEPC uses previously accumulated resources to subsidize the price and keep it within the band.

The 84- and 90-octane gasolines, as well as 84-octane gasohol, were incorporated into this

fund in March 2022 and remained there until December of the same year. Although 90- and 95-octane gasohol were not incorporated into the band, the inclusion of 90-octane gasoline could affect the price of 90-octane gasohol, because gasoline is its main input. Consequently, the estimated elasticity must be interpreted within the price framework in place during the period analyzed, and the results should not necessarily be extrapolated to other scenarios.

In addition, 84- and 90-octane gasolines and gasohols, together with different types of diesel, were temporarily exempted from the ISC between April and June 2022 because the government feared that their price increase would disproportionately affect the basic consumption basket. Although the government initially stated that it would evaluate whether to extend the measure, it ultimately decided to maintain June as the end date after not observing the desired results.

Figure 1: Monthly evolution of gasohol demand and real prices in LMC, 2020-2022



Note: The indices take the first observed month as the base (=100). The vertical lines indicate the beginning of COVID-19 restrictions and the period of temporary ISC exemption.

Source: Author's elaboration based on Osinergmin data.

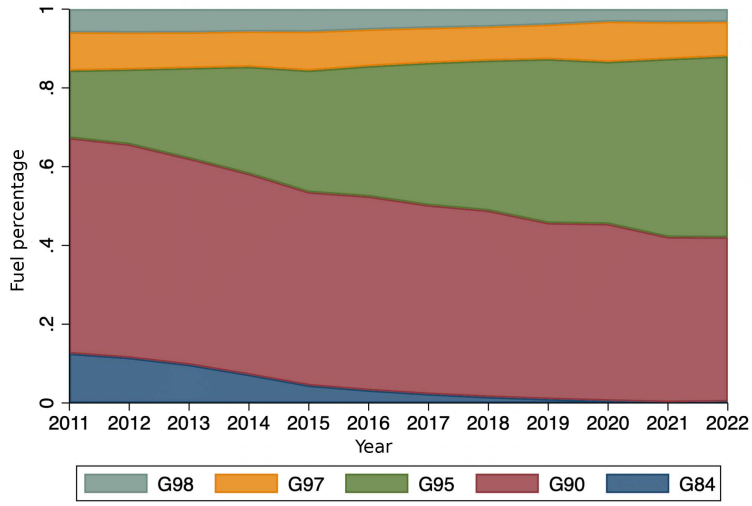
These interventions are relevant for interpreting the results because they may have temporarily modified the transmission between international oil prices, local prices, and quantity demanded. In particular, the incorporation of some fuels into the FEPC and the temporary ISC exemption introduced stabilization or price-reduction mechanisms that do not respond exclusively to supply and demand conditions.

Regarding the characteristics of the gasohol market, Osinergmin data indicate that, as of December 2022, LMC represented 39% of national demand for gasohol sold to the public, a share greater than the proportion of the national population living in LMC. National gasohol demand for all uses follows a similar pattern: LMC also represented 39%. In addition, 98.4% of LMC gasohol demand corresponds to sales to the public through service stations, a figure similar to the national share of 98.5%.

Thus, demand in LMC represents an important share of national gasohol demand, both for public sales and all uses. More importantly, gasohol has a particular feature: while gasoline is used across several industries, 98.4% of gasohol is used for vehicular consumption, so its demand is relatively isolated from demand in other sectors. This is an advantage for the estimation because, otherwise, it would be necessary to design a tool to distinguish between these demands.

The vehicle fleet in LMC is composed mainly of cars, which represented 42% of total vehicles in the city as of December 2022, according to data from the Ministry of Transportation. Other important vehicle categories are motorcycles and station wagons, representing 23% and 6% of the total vehicle fleet. This information is relevant because each type of vehicle tends to use a different type of fuel. While most cars use G90 and G95, station wagons use diesel or petroleum, and motorcycles use 84-octane gasohol (Ministerio del Ambiente, 2021). Consequently, in practice, this analysis focuses on fuels specifically associated with cars, which are used for private transportation and taxi services.

Figure 2: Percentage share of gasohol demand in LMC, 2011-2022



Source: Author's elaboration based on Osinergmin data.

This paper uses districts as the empirical unit because quantity data are available at that level. However, a district does not necessarily coincide perfectly with the relevant economic market for fuel purchases. Urban mobility evidence for LMC shows that the city functions as an integrated metropolitan space, with daily trips across districts for work, education, and personal reasons. The district should therefore be understood as an operational approximation to the local market, determined by data availability, rather than as a perfect delimitation of the relevant economic market.

In particular, the Origin-Destination Household Travel Survey of the Urban Mobility Plan for LMC (Autoridad de Transporte Urbano para Lima y Callao, 2023) records trips made by households in the metropolitan area, making it possible to observe that mobility patterns are not restricted to district boundaries. This interpretation is consistent with additional evidence on the intensity of urban travel in LMC: the 2024 TomTom ranking

reports a congestion level of 47% for Lima, while information from the 2023 Urban Mobility Plan cited by AFIN records, on a working day, 8,052 trailer trips, 772 truck trips, and 30,619 small-truck trips in LMC (Asociación para el Fomento de la Infraestructura Nacional, 2025).

Likewise, the spatial distribution of service stations should not be interpreted as random. Higher or lower competition among service stations may be related to structural district characteristics such as urban density, traffic intensity, commercial activity, road connectivity, proximity to employment areas, or mobility patterns. These characteristics may also directly influence the quantity demanded of gasohol. For this reason, spatial competition is interpreted as a local characteristic of exposure to fuel cost shocks and reference prices, whose validity as a component of the instrument is discussed in greater detail in the methodology section.

Finally, as a consequence of Supreme Decree DS 006-2022-EM (Ministerio de Energía y Minas, 2022), since January 2023, and nationwide with the exception of Loreto and Ucayali, Peru sells only two gasoline octane categories: regular (91 octanes) and premium (96 octanes). The objective of this measure is to reduce the number of available octane types and organize the national gasohol market, while discontinuing the sale of fuels considered too polluting. As a result of this policy change, the numerical values estimated here can only be used to evaluate the local market retrospectively.

3 Literature Review

Empirical estimates of the price elasticity of gasoline demand are highly volatile, as shown in Table 6. This volatility, which results from several factors, was studied by Galindo et al. (2015), who conducted a meta-analysis for Latin America and concluded that the main sources of distortion are differences across regions or countries, the time horizon considered, and the estimation method applied.

Regional differences are important because there is a positive relationship between development level and gasoline demand elasticity (McRae, 1994; Liddle and Huntington, 2020). This is because consumers in developed countries have greater substitutability between private and public transportation (Goodwin et al., 2004), a wider supply of vehicles using fuels other than gasoline (Pock, 2007), and a more diversified energy supply, a factor that significantly affects elasticity (Lin and Zeng, 2013).

The time horizon is also relevant because gasoline demand is particularly sensitive to price in the long run (Rogat and Sterner, 1998). This result is consistent with estimates such as those of Eltony (1996), Sipes and Mendelsohn (2001), Pock (2007), and Flood et al. (2010). Moreover, Aklilu (2020) conducts a meta-analysis of price elasticity of demand across countries and concludes that elasticity is higher in the long run, drawing on Espey (1998), Graham and Glaister (2002), Basso and Oum (2007), and Brons et al. (2008). It is also worth noting that time matters because, according to Hanly et al. (2002), elasticity increases over time. Although it is difficult in the short run to substitute gasoline consumption with other fuels, in the long run consumers can transition between energy sources.

Finally, Galindo et al. (2015) concludes that panel-data or cross-sectional estimates commonly obtain smaller coefficients than time-series estimates. This observation is relevant for the present paper because the study uses district-level panel data with district and month fixed effects, implying that the estimated elasticities may differ from those obtained using aggregate time series for the entire country.

Regarding taxes, the literature has found that their impact on elasticity is not strong (Sipes and Mendelsohn, 2001; Flood et al., 2010) and depends on the type of tax (Sipes and Mendelsohn, 2001; Hanly et al., 2002). This is crucial because, otherwise, the introduction of taxes would simultaneously affect price and gasoline demand elasticity, making it more difficult to determine the final effect of the policy on quantity demanded. With respect to the impact on price, Baranzini and Weber (2013) find that the effect is significant, although a substantial increase is required to achieve the type of reduction needed to meet environmental targets (Kayser, 2000; Aklilu, 2020).

For Peru, Rogat and Sterner (1998) use time series to estimate the short-run price elasticity of gasoline demand at -0.200 and the long-run elasticity at -0.49 for the period 1960–1994. The authors also note that, unlike other oil-producing countries,[1] Peru had one of the highest elasticities in the region. Complementarily, Cordano Vásquez et al. (2005) use data for 1994–2003 and estimate an ARDL model. They find short- and long-run price elasticities for 84-, 90-, and 97-octane gasoline of 0.33, 0.45, and -1.09, and -0.648, -0.849, and -1.693, respectively. Although some short-run signs are not consistent with a negative demand relationship, the long-run pattern is consistent with price-sensitive demand and greater sensitivity for higher-octane fuels. In this line, the authors conclude that 97-octane gasoline is more sensitive to price changes and argue that 84- and 90-octane gasoline may act as substitutes when the price of higher-octane gasoline increases.

A common thread among these factors is that they determine greater or lower substitutability for the product: in developed countries, consumption alternatives are more varied, and in the long run it is possible to make more changes in consumption than in the short run, when numerous rigidities are present. Therefore, elasticity can be expected to be largely determined by the degree of substitutability of the good.

4 Data

4.1 Prices and spatial competition

Since 2015, all agents commercializing hydrocarbon-derived fuels must report, whenever a price change occurs, the price at which they sell these fuels in Osinergmin's Order Control System (*Sistema de Control de Órdenes de Pedido*, SCOP). This information allows the agency to publish a monthly report of average prices in each department of Peru, as well as for Metropolitan Lima and Callao. In addition to this report, since 2020 Osinergmin has annually published a database containing all prices reported by retail establishments

[1] Venezuela had a short-run price elasticity of demand of -0.39 and Bolivia of -0.16. Mexico had the highest elasticity, with a value of -1.71.

for each fuel type sold.

The database also contains the date on which each price was modified and the exact location of the service station, which was later geolocated. This information made it possible to construct not only the price variable, but also a variable capturing the level of spatial competition faced by each service station. The database contained information for 803 service stations distributed across LMC, a number that remains constant throughout the period analyzed.

For prices, we obtained a monthly district average, weighting reported prices by the length of time they remained in force before being updated again. Because information on the quantity sold by each station is private and Osinergmin is therefore not authorized to share it, the price variable is not weighted by each station's relative importance in terms of quantity sold. This is a limitation in the construction of the variable, but it still provides a useful approximation of the price level in each district.

We therefore obtained an initial database containing the average price of G90 and G95 for the LMC districts with available price and quantity information between March 2020 and December 2022.

Because prices were expressed in nominal terms, while economic agents make demand decisions based on real prices, we deflated prices using the consumer price index (CPI) for vehicular fuel in LMC. This series was obtained from INEI's website and uses December 2021 as the base.

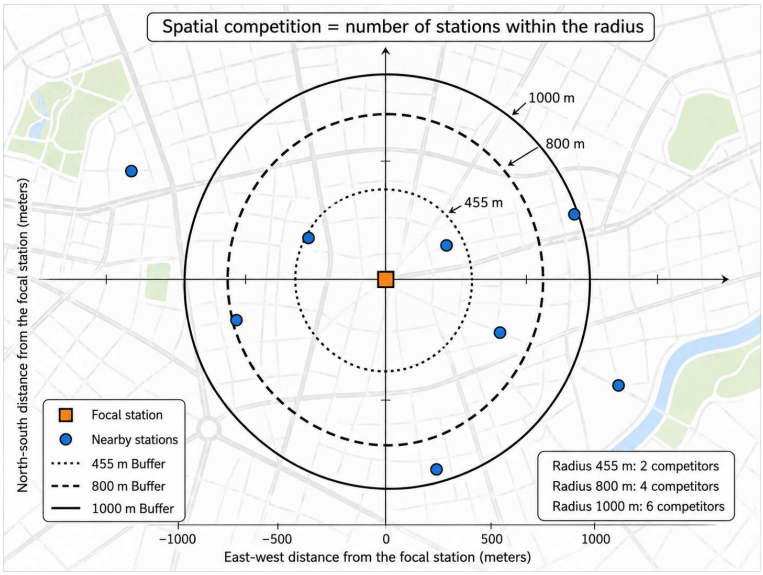
For spatial competition, we calculated for each service station in the Osinergmin database the number of other service stations located within different distance radio. In particular, spatial competition measures were constructed for radio of 455, 800, and 1,000 meters. These variables allow the analysis to evaluate whether the results depend on a specific definition of the local market around each service station. In the instrumental-variable exercises, the 1,000-meter radius produced the best diagnostic for 90-octane gasohol, while the other radio are used as alternative sensitivity specifications. The values were then averaged at the district level to obtain a new variable capturing the average number of competitors faced by service stations in each district.

4.2 Quantity

Quantity information comes from monthly reports published by Osinergmin. For each district and fuel grade, the quantity variable records average daily sales during the corresponding month, expressed in gallons per day. Thus, the observations have monthly frequency, while quantities are measured as daily averages rather than monthly totals. This study uses observations from March 2020 to December 2022.

We then used information from the Osinergmin price report to determine the number of service stations in each district. Dividing district-level average daily sales of each fuel grade by the number of service stations yields a complementary descriptive measure of daily sales per station. The main quantity variable used in the regressions remains

Figure 3: Spatial competition buffers around service stations



Note: The data were inspected using address, latitude, and longitude, and then geolocated.

Source: Author's elaboration based on Osinergmin data.

district-level average daily sales, measured in gallons per day for each product and month.

4.3 Complementary controls

For the instrumental-variable exercises, we incorporated monthly series of fuel reference prices published by Osinergmin. In particular, we used reference prices associated with 90- and 95-octane gasohol to construct cost shocks closer to the Peruvian market than international crude-oil benchmarks.

From these series, we constructed lags and logarithmic variations of reference prices. These shocks are used only in the instrumental-variable diagnostic exercises and are not part of the main demand specification.

Monthly lags of up to twelve months were constructed from the fuel reference price series. These lags are used only in the methodological instrumental-variable exercises, with the objective of evaluating possible delays in the transmission of cost shocks to local prices. The specific lag used in each exercise is discussed in the methodology section.

Initial district-level consumption shares of 90- and 95-octane gasohol capture the local market composition, while variations in reference prices capture product-level cost shocks. This index is then interacted with measures of local spatial competition to capture heterogeneous exposure across districts.

In addition, aggregate variables were incorporated to describe and control for the macroeconomic and sanitary context of the period. These include economic activity, proxied by monthly GDP published by the Central Reserve Bank of Peru (BCRP); vehicle flow from

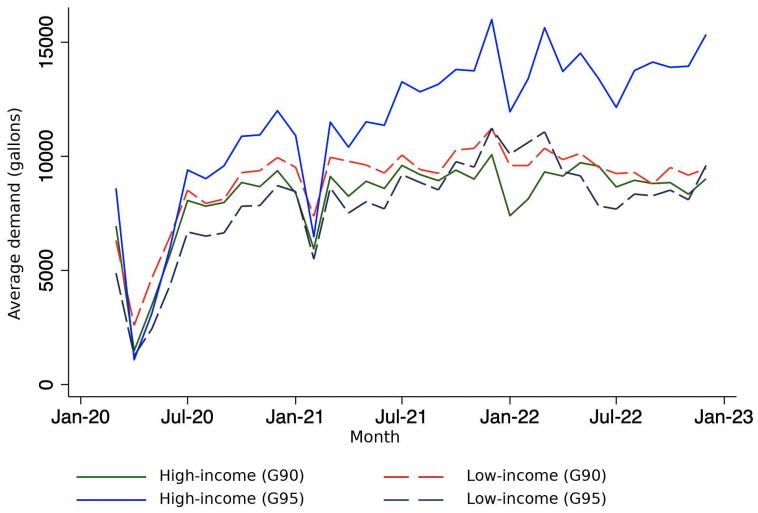
the monthly vehicle-flow bulletins of the National Institute of Statistics and Informatics (INEI); COVID-19 restrictions proxied by the Oxford COVID-19 Government Response Tracker stringency index; and the nominal sol-dollar exchange rate from the BCRP. These variables have monthly frequency and vary only at the aggregate level, so they do not present district-level variation within a given month. In the main specification with month fixed effects, these variables are absorbed by period effects and are therefore used mainly in complementary exercises without month fixed effects and as part of the contextualization of the 2020-2022 period.

4.4 Income level

To capture each district's income level, we use the position obtained by each district in the 2018 Provincial and District Monetary Poverty Map ranking (National Institute of Statistics and Informatics, 2020), which orders all districts in Peru from poorest to richest using information collected during the 2017 Census. We prefer the national ranking to the provincial ranking because it better captures the large variation in purchasing power across LMC districts.

The district unit used in this study corresponds to the location where fuel sales are recorded and not necessarily to the consumer's district of residence. The observed quantity should therefore be interpreted as sales carried out in the district, rather than as consumption exclusively by residents of that district. This distinction is important because consumers may purchase fuel in districts other than their district of residence, especially near district borders, road corridors, or areas with a high concentration of service stations. Thus, district income is not interpreted as a perfect measure of the income of all observed buyers, but as an approximation of the local socioeconomic environment in which sales take place.

Figure 4: Gasohol consumption by octane level and income level, 2020-2022



Source: Author's elaboration based on Osinergmin data.

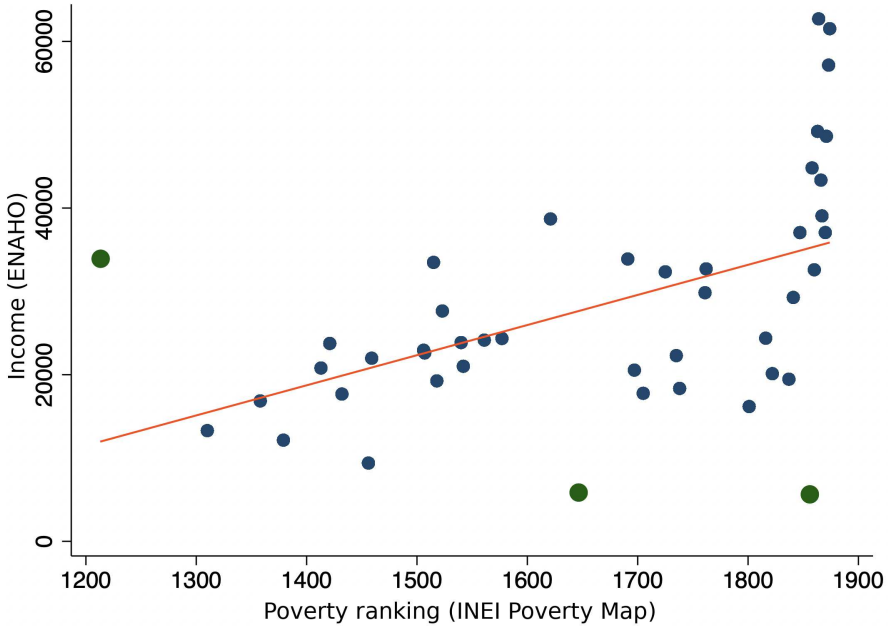
The use of a ranking as an indicator of district income has the disadvantage of being or-

dinal rather than cardinal: the distance between two consecutive positions in the ranking does not necessarily represent the same difference in income or poverty. The implications of this issue are discussed in Section 5.

To complement this choice, Figure 5 shows the dispersion between each district's position in the ranking and its average income between 2020 and 2022 according to the National Household Survey (ENAHO). Although this survey does not allow district-level inference in LMC, the observed data show a positive relationship between both variables, suggesting that the ranking is a useful way to capture each district's purchasing power.

The values corresponding to three outliers are highlighted in green. On the one hand, the district of Ventanilla has a high ENAHO income value relative to its position in the poverty ranking. On the other hand, the opposite occurs in La Punta and San Bartolo.

Figure 5: Correlation between income and poverty ranking



Note: The figure shows the relationship between each district's average annual nominal wage between 2020 and 2022 according to ENAHO and the ranking position obtained in the 2018 poverty map.

Source: Author's elaboration based on ENAHO and INEI data.

4.5 Final database

After separately constructing each of the variables needed to estimate the demand equation, we merged the information. The resulting database is a monthly district-product panel containing quantities sold and real prices for 90- and 95-octane gasohol between March 2020 and December 2022.

As shown in Table 1, the database contains information for all districts included in the sample after excluding five districts with problems in price reporting. It is also worth noting that 95-octane gasohol has both a higher average price and a higher average quantity. Both facts are expected, given that this product is usually sold at a higher price because of its higher quality and because its consumption has increased steadily since 2010 according to Ministerio del Ambiente (2021).[2]

The standard deviation of income level is also noteworthy, and may be considered high given that LMC has only 50 districts. This indicates substantial inequality in purchasing power across districts.

[2]For more detail, see Figure 2.

Table 1: Descriptive Statistics: Dataset

	Mean	Standard Deviation	N
Real price			
Gasohol 90	15.25	2.91	1631
Gasohol 95	16.58	3.19	1641
Total	15.92	3.12	3272
Quantity			
Gasohol 90	4825.55	4539.39	1631
Gasohol 95	5536.12	5701.51	1641
Total	5181.92	5166.53	3272
District characteristics			
Spatial competition 455m	4.26	3.01	3272
Spatial competition 800m	6.79	3.97	3272
Spatial competition 1000m	8.99	5.31	3272
District poverty ranking	1657.98	183.52	3272
Osinergmin reference prices			
PRC Gasohol 90	90.57	31.47	3272
PRC Gasohol 95	94.90	32.77	3272
Aggregate controls			
Monthly GDP, year-on-year var.	2.64	17.72	3272
Lima vehicle flow, log	5.51	0.30	3272
COVID-19 stringency	56.73	22.83	3272
PEN/USD exchange rate	3.76	0.19	3272

Note: Statistics are calculated over the main estimation sample, defined by district-product-month observations. Local prices are expressed in real terms. Spatial competition measures indicate the average number of service stations located within each radius around the gas stations in the district. Osinergmin reference prices are reported as source variables; their lags and logarithmic transformations are discussed in the methodology section.

Source: Own elaboration.

5 Methodology

This study estimates the demand elasticity for G90 and G95 using, as its main source of information, data on the quantity sold of each product and the price at which these transactions occur. According to economic theory, these data represent the equilibrium reached through the interaction of supply and demand forces in the corresponding market.

In response to this issue, we follow the recommendation of Goldberger (1991) for demand estimation and consider instrumental variables. Specifically, the study proposes using an instrument adapted from the traditional Bartik instrument, also known as a shift-share instrumental variable (SSIV), named by Bartik (1991) and popularized by Blanchard et al. (1992). In its canonical configuration, this instrument is used to estimate labor supply elasticity, but Goldsmith-Pinkham et al. (2020) show that its use can be extended to other contexts.

As a precaution, the paper also adopts an alternative empirical strategy, ultimately presented as the main specification, which estimates the relationship between prices and quantities using a log-log model with district and month fixed effects. This specification does not eliminate all possible sources of endogeneity, but it controls for persistent structural differences across districts and common shocks affecting all districts in each month. The instrumental-variable exercises are presented as an additional methodological diagnostic, with the objective of evaluating whether it is possible to isolate price variation associated with fuel cost shocks. These exercises are not presented as the preferred estimate if the first-stage and reduced-form diagnostics do not allow a consistent economic interpretation.

5.1 Main specification: log-log model with fixed effects

The main specification is a log-log regression of quantity demanded on the real price of gasohol. The model is estimated separately for 90- and 95-octane gasohol, and pooled specifications are also reported as a reference. The baseline equation is:

$$\ln Q_{ipt} = \beta \ln P_{ipt} + \alpha_i + \gamma_t + \varepsilon_{ipt} \tag{1}$$

where $\ln Q_{ipt}$ represents the natural logarithm of average daily sales of gasohol product p in district i during month t, measured in gallons per day; $\ln P_{ipt}$ represents the natural logarithm of the corresponding real price; α_i denotes district fixed effects; γ_t denotes month fixed effects; and ε_{ipt} is the error term. Observations have monthly frequency. Standard errors are clustered at the district level to allow for serial correlation and other within-district dependence in the error term.

The log-log specification expresses the relationship between prices and quantities in percentage terms. In this model, the coefficient β measures the approximate percentage change in average daily sales associated with a 1% increase in the real price, holding district and month fixed effects constant. Because these controls do not eliminate all potential sources of price endogeneity, β is interpreted as a conditional price–sales association

rather than an identified causal demand elasticity. The slope in logarithms is expressed as:

$$\frac{\partial \ln Q_{ipt}}{\partial \ln P_{ipt}} = \beta \tag{2}$$

District fixed effects control for persistent characteristics of local markets, such as urban density, socioeconomic composition, road infrastructure, structural mobility patterns, and the relative availability of service stations. Month fixed effects absorb shocks common to all districts in the same period, such as COVID-19 restrictions, macroeconomic variation, general price changes, changes in aggregate mobility, and exceptional measures in the fuel market.

We estimate specifications for the full 2020-2022 sample and for the 2021-2022 subperiod. The second sample evaluates whether the results hold when excluding the period most affected by the initial mobility shock associated with COVID-19.

5.2 Complementary specifications and sensitivity checks

5.2.1 Aggregate controls

As a complementary exercise, we estimate models incorporating aggregate controls for economic activity, mobility, and sanitary restrictions. Specifically, we consider monthly GDP, Lima vehicle flow, the COVID-19 restriction stringency index, and, when appropriate, the nominal sol-dollar exchange rate. These variables make it possible to describe and control for the macroeconomic and sanitary context of the period analyzed.

Because these variables have monthly frequency and no district-level variation within a given month, they cannot be identified simultaneously with month fixed effects. Therefore, the models with aggregate controls are estimated as complementary specifications without month fixed effects. The general equation is:

$$\ln Q_{ipt} = \beta \ln P_{ipt} + \theta X_t + \alpha_i + \delta_p + \varepsilon_{ipt} \tag{3}$$

where X_t represents the set of aggregate controls in month t; α_i denotes district fixed effects; and δ_p represents product fixed effects in pooled specifications. In product-specific estimates for G90 and G95, product fixed effects are not included because the sample contains a single product. These specifications do not replace the main model, but serve to evaluate the sensitivity of the results when explicitly controlling for aggregate variables that, in the main specification, are absorbed by month fixed effects.

5.2.2 Interaction between district income and time blocks

As a robustness check against the possibility that higher- and lower-income districts followed different trajectories during the period analyzed, we estimate a specification that interacts district income with quarterly or semiannual time effects. This test seeks to capture differential trends by socioeconomic level that could be correlated with spatial

competition or with heterogeneous recovery after the initial COVID-19 shock. Since district income is time-invariant, its direct effect is absorbed by district fixed effects; however, its interaction with time blocks allows the specification to control for whether districts with different income levels evolved differently over the period.

$$\ln Q_{ipt} = \beta \ln P_{ipt} + \alpha_i + \gamma_t + \sum_s \lambda_s \left(\ln Y_i \times S_s\right) + \delta_p + \varepsilon_{ipt} \tag{4}$$

where S_s represents quarterly or semiannual time blocks, and $\ln Y_i \times S_s$ captures differentiated trajectories according to district income. In product-specific estimates, the product fixed effect δ_p is not included. This specification does not replace the main model, but functions as a sensitivity check against the possibility that the relationship between prices, quantities, and spatial competition is partly influenced by district-level socioeconomic trends.

5.3 Instrumental-variable exercises

In this setup, we explore instrumental-variable exercises. The logic of the instrument is to combine product-level reference price shocks with the initial consumption composition of each district. For each district i, we calculate the initial consumption shares of 90- and 95-octane gasohol, denoted as $shareG90_i$ and $shareG95_i$. Then, for each month t and lag l, we construct a shift-share component of reference prices:

$$B_{it}^{(l)} = shareG90_i \times \Delta \ln(PRC_G90_{t-l}) + shareG95_i \times \Delta \ln(PRC_G95_{t-l}) \tag{5}$$

where $\Delta \ln(PRC_G90_{t-l})$ and $\Delta \ln(PRC_G95_{t-l})$ represent lagged logarithmic variations in Osinergmin reference prices for 90- and 95-octane gasohol. The initial shares capture each district's relative exposure to cost shocks for each gasohol type.

This component is then interacted with measures of local spatial competition. For each radius $r \in \{455, 800, 1000\}$ meters, the instrument is defined as:

$$Z_{it}^{(l,r)} = B_{it}^{(l)} \times Competition_i^{(r)} \tag{6}$$

where $Competition_i^{(r)}$ represents the average number of competitors within radius r around service stations in district i. This interaction seeks to capture the idea that the same cost shock may be transmitted differently to local prices depending on the level of spatial competition in each district.

To allow for delays in the transmission of cost shocks to final prices, lags of one to twelve months are constructed for reference prices. Evaluating different lags makes it possible to analyze whether the relationship between cost shocks and local prices depends on transmission timing. In the diagnostic exercises, combinations of lags and spatial competition radio are compared without assuming *a priori* that a single combination is necessarily valid for all products.

Although the instrument shares the general structure of the Bartik (1991) approach by interacting a common exogenous shock with a local characteristic that determines exposure intensity, this application should not be interpreted as a strict SSIV.

According to Borusyak et al. (2022), the SSIV framework typically requires the presence of multiple quasi-random shocks that are not correlated with each other, as well as an exposure structure that makes it possible to interpret the shares as plausibly exogenous sources of variation. In this estimation, by contrast, the instrument uses a small number of product-level shocks and a fixed local exposure characteristic.

5.4 First stage, reduced form, and second stage

To evaluate instrument performance, We estimate three relationships: the first stage, the reduced form, and the IV second stage. These exercises are reported as methodological diagnostics and do not replace the main specification.

The first stage evaluates whether the instrument is correlated with the local real price:

$$\ln P_{ipt} = \pi Z_{it}^{(l,r)} + \alpha_i + \gamma_t + \eta_{ipt} \tag{7}$$

where $\ln P_{ipt}$ is the logarithm of the real price of product p in district i and month t, and $Z_{it}^{(l,r)}$ is the instrument constructed with lag l and competition radius r. Instrument relevance is evaluated through the sign, magnitude, and F-statistic associated with the coefficient π.

The reduced form evaluates whether the instrument is related to quantity demanded:

$$\ln Q_{ipt} = \rho Z_{it}^{(l,r)} + \alpha_i + \gamma_t + \nu_{ipt} \tag{8}$$

This equation indicates whether the variation induced by the instrument moves in a direction consistent with a negative relationship between price and quantity.

Finally, the IV second stage estimates the relationship between quantity demanded and the instrumented price:

$$\ln Q_{ipt} = \beta \widehat{\ln P}_{ipt} + \alpha_i + \gamma_t + \varepsilon_{ipt} \tag{9}$$

where $\widehat{\ln P}_{ipt}$ is the fitted value of price obtained in the first stage. As in the main specification, district and month fixed effects are included and standard errors are clustered at the district level.

5.5 Validity and interpretation of the IV exercises

The validity of the identification strategy depends essentially on the validity of the constructed instrument. For this justification, we first analyze separately each component of

the instrument and its potential problems.

The first component corresponds to shocks in 90- and 95-octane gasohol reference prices published by Osinergmin. These prices capture variations in reference costs relevant to the Peruvian fuel market. They are therefore expected to be related to observed local prices. However, because these reference prices may also reflect institutional conditions, updating rules, and price-stabilization mechanisms, their validity as a source of exogenous variation must be evaluated empirically rather than assumed automatically.

The exclusion restriction requires reference price shocks to affect quantity demanded only through their effect on local prices. This assumption is demanding in the context analyzed because the period coincides with the COVID-19 pandemic, price-stabilization measures, temporary ISC exemptions, and changes in mobility. For this reason, the instrumental-variable exercises are interpreted as identification diagnostics rather than definitive evidence of causality.

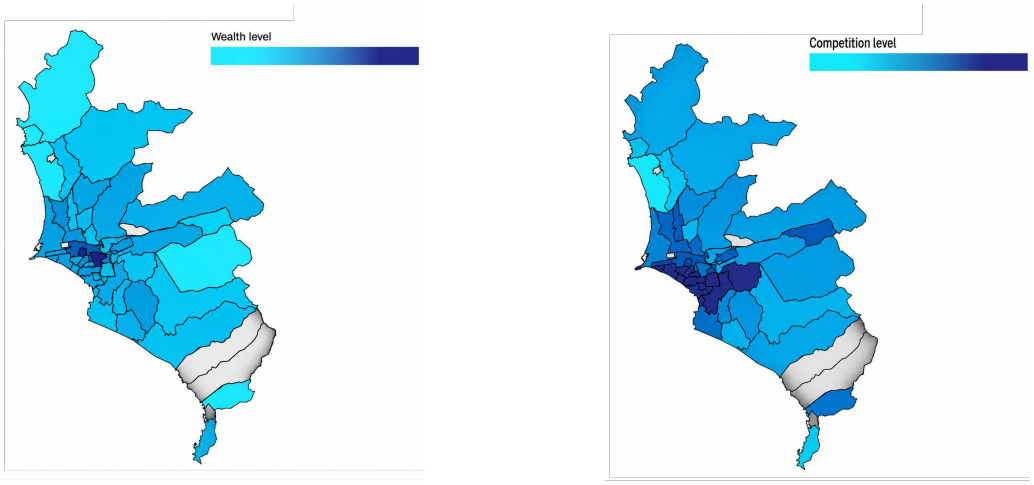
The use of lags responds to the possibility that changes in reference costs are not immediately transmitted to final prices. Monthly lags of up to twelve months are therefore constructed and their performance is evaluated in the first stage and reduced form. The selection of a specific lag is not imposed solely by theory, but is evaluated empirically within the reported diagnostics.

The second component of the instrument is spatial competition, which measures the average number of service stations faced by stations in each district. Assuming that this variable has a real and pronounced effect on the price charged by a station is reasonable in light of the literature, which shows a negative relationship between a station's price and the number of other stations located nearby (Clemenz and Gugler, 2009; Pennerstorfer, 2009; Houde, 2012; Cardoso et al., 2022). The explanation provided in this literature is that, if stations are sufficiently close, they compete, so that the greater the number of stations within a given radius, the lower the price charged by stations within that area.

This supports the assumption that the number of service stations reflects the level of competition faced by stations in a district and that this, in turn, affects the price at which a station offers its products. This means that the variable can satisfy the relevance condition. However, the exclusion restriction is more problematic, because there are several possible sources of endogeneity: spatial competition may incorporate factors that also influence demand decisions. For example, service stations may tend to concentrate in areas with high long-run demand. This would violate the exclusion restriction and would make the instrument invalid if used without caution.

Another possible source of endogeneity can be observed in Figures 6a and 6b, which show income level and competition level in each district. In these maps, the spatial coloration patterns in LMC coincide, indicating a relationship between income and spatial competition. In other words, districts with greater purchasing power also tend to have more nearby service stations. This is an important threat to identification because the instrument may be capturing socioeconomic differences across districts rather than only heterogeneous exposure to cost shocks.

Figure 6: Level map for LMC districts



(a) Monetary wealth (2018) (b) Competition (2020-2022)

Note: The map shows in darker shades the districts in which the illustrated variable reaches a higher level. The districts omitted from the database are shown in gray.

Source: Author's elaboration. Data extracted from INEI (a) and Osinergmin (b).

For this reason, the empirical analysis includes district fixed effects and month fixed effects, and the robustness section adds interactions between district income and time blocks. These exercises are designed to address the possibility that districts with different income levels followed different trajectories during the period analyzed. Nevertheless, because spatial competition is a local structural variable, the validity of the instrument cannot be fully guaranteed by these controls. The IV results should therefore be interpreted cautiously and as diagnostic exercises rather than as the preferred causal estimates.

6 Results

Table 2 presents the main results of the paper. The preferred specification corresponds to the log-log model estimated by ordinary least squares with district and month fixed effects. The coefficient of interest is the elasticity of demand with respect to the real price of gasohol.

Table 2: Main results: price elasticity of gasohol demand

	Full sample		2021–2022	
	G90	G95	G90	G95
ln(*Real price*)	-1.498**	-2.199***	-2.465***	-3.175***
	(0.639)	(0.455)	(0.841)	(0.631)
District fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	1629	1641	1150	1163

Note: The dependent variable is the logarithm of the monthly quantity of gasohol sold. Prices are expressed in real terms. Standard errors, clustered at the district level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results indicate a negative relationship between the real price and quantity demanded. In the full sample, the estimated elasticity is -1.50 for 90-octane gasohol and -2.20 for 95-octane gasohol. These values imply that a 1% increase in real price is associated with a 1.50% decrease in the quantity demanded of G90 and a 2.20% decrease in the quantity demanded of G95, holding district and month fixed effects constant.

When the sample is restricted to the 2021-2022 period, the estimated elasticities become larger in absolute value. The elasticity for G90 is -2.46, while the elasticity for G95 reaches -3.17. This pattern suggests that the initial months of the pandemic, characterized by strong mobility restrictions and abnormal demand behavior, may have attenuated the relationship between prices and quantities in the full sample.

These estimates should not be interpreted as unconditional or fully structural elasticities. Instead, they reflect the association between local real prices and quantities sold after controlling for persistent district characteristics and common monthly shocks. The interpretation remains conditional on the exceptional institutional and macroeconomic context of the period.

Table 3 reports specifications that include aggregate controls for economic activity, mobility, sanitary restrictions, and exchange-rate variation. Because these variables vary only by month, the models do not include month fixed effects. The purpose of this exercise is to evaluate whether the negative relationship between price and quantity persists when explicitly controlling for the aggregate context of the period.

Table 3: Complementary specifications with aggregate controls

	Pooled	G90	G95
ln(*Real price*)	-0.597***	-0.574***	-0.803***
	(0.074)	(0.060)	(0.095)
Monthly GDP, year-on-year var.	0.006***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)
ln($Vehicle\ flow$)	0.761***	0.637***	0.883***
	(0.031)	(0.040)	(0.034)
COVID-19 stringency	-0.007***	-0.005***	-0.010***
	(0.001)	(0.001)	(0.001)
District fixed effects	Yes	Yes	Yes
Product fixed effects	Yes	No	No
Month fixed effects	No	No	No
Observations	3272	1631	1641

Note: The dependent variable is the logarithm of the monthly quantity of gasohol sold. These specifications do not include month fixed effects, since the aggregate controls vary at the monthly level and would be absorbed by those fixed effects. Standard errors, clustered at the district level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results remain negative across specifications, although the magnitudes vary. This is expected because the models without month fixed effects identify the effect using a different source of variation and explicitly include aggregate variables that, in the main specification, are absorbed by monthly fixed effects. These specifications therefore serve as complementary checks rather than substitutes for the preferred model.

Table 4 presents robustness checks that interact district income with quarterly or semi-annual time blocks. These interactions address the possibility that districts with different socioeconomic levels experienced different trajectories during the pandemic and recovery period.

The results remain broadly consistent with the main findings. This suggests that the estimated negative relationship between price and quantity is not driven exclusively by differential time paths across richer and poorer districts. Nevertheless, these controls should be interpreted as sensitivity checks rather than as definitive tests of all possible threats to identification.

Table 5 reports the instrumental-variable diagnostic exercise for the specification that produces the most coherent pattern among those evaluated: the PRC shift-share instrument for G90 in 2021-2022. The table presents the first stage, reduced form, and second stage.

The first stage indicates whether the instrument is relevant for local prices. The reduced form indicates whether the instrument is related to quantity demanded in the expected direction. The IV estimate is reported only as a diagnostic and should not be interpreted as the preferred causal estimate unless the first-stage and reduced-form signs support a consistent economic interpretation.

Table 4: Robustness: interaction between district income and time blocks

	Full sample		2021–2022	
	G90	G95	G90	G95
Panel A: District income × quarter				
ln(Real price)	-1.456**	-1.963***	-2.503***	-2.958***
	(0.644)	(0.402)	(0.836)	(0.595)
Panel B: District income × semester				
ln(Real price)	-1.586**	-2.076***	-2.598***	-3.032***
	(0.620)	(0.415)	(0.857)	(0.582)
District fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Income × time interaction	Yes	Yes	Yes	Yes
Observations	1629	1641	1150	1163

Note: The dependent variable is the logarithm of the monthly quantity of gasohol sold. All specifications include district and month fixed effects. Panel A interacts district income with quarterly blocks, while Panel B interacts it with semester blocks. Standard errors, clustered at the district level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Instrumental variables diagnostic: PRC shift-share, G90 2021–2022

	OLS	First stage	Reduced form	IV
	$\ln Q$	$\ln P$	$\ln Q$	$\ln Q$
ln(*Real price*)	-2.465***			5.940
	(0.841)			(4.345)
PRC shift-share instrument		-0.00420***	-0.0250*	
		(0.00127)	(0.0148)	
Constant	14.94***	2.806***	8.046***	
	(2.357)	(0.000665)	(0.00774)	
District fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	1150	1150	1150	1150

Note: The instrument corresponds to the specification *z_bartik_dprc_l*8_1000, constructed from lagged logarithmic changes in Osinergmin reference prices for G90 and G95, initial consumption shares by district, and spatial competition within 1000 meters. The table is presented as a methodological diagnostic. Although the first stage is statistically relevant and the reduced form is negative, the sign of the first stage implies that the IV estimate does not produce an interpretable negative price-demand elasticity. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In this exercise, the diagnostic evidence does not provide a sufficiently robust basis to adopt the IV coefficient as the preferred estimate. In particular, the IV result does not

generate a negative demand elasticity that can be interpreted consistently with the underlying economic model. For this reason, the main interpretation of the paper relies on the fixed-effects log-log specifications, while the IV exercises are reported transparently as methodological diagnostics.

We also consider an Anderson-Rubin weak-instrument robust test. The test statistic is 2.73, with an approximate p-value of 0.105. Thus, at the conventional 5% level, the null hypothesis is not rejected. This result reinforces a conservative interpretation: the IV estimates should not be treated as definitive causal estimates of demand elasticity.

The appendix reports additional robustness exercises. These include searches over simple PRC instruments, PRC shift-share instruments, temporal robustness checks, and alternative functional specifications. The objective is not to select a preferred instrument mechanically, but to document the sensitivity of the results and the methodological limitations of attempting to isolate exogenous price variation in this market.

The additional exercises confirm that the main negative relationship between price and quantity is robust in the fixed-effects demand specifications. However, the IV diagnostics are sensitive to the choice of lag, radius, and product. This sensitivity is consistent with the discussion of identification challenges: the period analyzed was affected by the pandemic, policy interventions, and heterogeneous local recovery patterns.

7 Conclusions

The objective of this paper is to estimate the price elasticity of demand for 90- and 95-octane gasohol in Metropolitan Lima and Callao for the period from March 2020 to December 2022. The evidence shows that gasohol demand responds negatively to changes in real prices. In the main fixed-effects specification, the elasticity is -1.50 for G90 and -2.20 for G95 in the full sample. When the analysis is restricted to 2021-2022, the estimated elasticities are -2.46 and -3.17, respectively.

These results suggest that fuel-tax policies such as the ISC may influence the quantity demanded of gasohol. However, the magnitude of the estimated effect should be interpreted with caution. The period analyzed coincides with the COVID-19 pandemic, changes in mobility, temporary ISC exemptions, and the operation of the Fuel Price Stabilization Fund. These factors may have altered the relationship between international fuel costs, local prices, and quantities demanded.

The results also reveal important differences between G90 and G95. Demand for 95-octane gasohol appears more sensitive to price changes, especially in the 2021-2022 subsample. This pattern may be related to differences in vehicle type, income level, district location, or consumption patterns. The descriptive evidence suggests that G95 consumption is more concentrated in higher-income districts, while G90 consumption is more broadly distributed.

The paper also explores an instrumental-variable approach inspired by the Bartik logic, using reference price shocks interacted with local spatial competition. These exercises

are useful as methodological diagnostics, but they do not provide sufficiently strong and consistent evidence to replace the fixed-effects estimates as the preferred specification. The IV results are sensitive to the choice of product, lag, and spatial competition radius, and the exclusion restriction remains demanding in the context analyzed.

The study has several limitations. First, the data are aggregated at the district level and do not allow the analysis of individual consumers or station-level quantities. Second, the district where fuel is sold does not necessarily correspond to the district of residence of the buyer. Third, the period analyzed is exceptional and may not reflect market behavior under normal conditions. Fourth, the post-2022 reform in the classification of fuels prevents a direct extension of the same product definitions beyond December 2022.

Future research could use more disaggregated data, ideally at the service-station or transaction level, to better capture local competition, cross-district purchasing behavior, and heterogeneous consumer responses. It would also be useful to analyze the market after the octane reform, once enough comparable data are available under the regular and premium categories. Finally, future policy evaluations should accompany fuel-tax reforms with explicit ex ante and ex post estimates of demand elasticity, especially when such policies seek to modify consumption patterns for environmental, fiscal, or distributive purposes.

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A Appendices

A.1 Review of elasticity estimates

Table 6: Matrix of Elasticities and Studies

Authors	Region	Interval	Period	Estimate
Al-Faris et al. (1997)	Bahrain	1970 - 1991	Long run	-1.780
Baltagi and Griffin (1983)	OECD(18)	1960 - 1978	Long run	-0.320
Baltagi and Griffin (1997)	OECD(18)	1960 - 1990	Long run	-0.380
Banfi et al. (2005)	Switzerland	1985 - 1987	Short run	-1.400
Bhattacharya and Blake (2009)	UAE	1982 - 2005	Long run	-1.064
Chakravorty et al. (2000)	Indonesia	1972 - 1992	Long run	-1.440
Chakravorty et al. (2000)	Iraq	1972 - 1992	Long run	-2.467
Chakravorty et al. (2000)	Qatar	1972 - 1992	Long run	-1.674
Cheung and Thomson (2004)	China	1980 - 1999	Short run	-0.190
Cordano Vásquez et al. (2005)	Peru	1994 - 2003	Short run	-1.090
Cordano Vásquez et al. (2005)	Peru	1994 - 2003	Long run	-1.693
Dahl et al. (1992)	Canada	1960 - 1985	Long run	-1.070
Dahl et al. (1992)	U.S.	1960 - 1985	Long run	-1.000
Dahl et al. (1992)	Greece	1960 - 1985	Long run	-1.120
Eltony (1996)	GCC	1975 - 1993	Short run	-0.110
Ferreira et al. (2009)	Brazil	2001 - 2003	Short run	-1.505
Flood et al. (2010)	OECD(23)	1978 - 2003	Long run	-1.080
Franzén and Sterner (2005)	Finland	1960 - 1986	Short run	-1.230
Franzén and Sterner (2005)	Netherlands	1960 - 1985	Long run	-2.290
Franzén and Sterner (2005)	Ireland	1960 - 1986	Long run	-1.680
Franzén and Sterner (2005)	OECD	1963 - 1985	Long run	-1.350
Goodwin et al. (2004)	OECD(18)	1974 - 1981	Short run	-0.350
González and Marrero (2012)	Spain	1998 - 2006	Long run	-2.837
Houthakker et al. (1974)	U.S.(48)	1974 - 1981	Long run	-0.230
Huntington (2010)	U.S.	1950 - 2005	Short run	-0.277
Kayser (2000)	U.S.	1981	Short run	-0.230
Liddle and Huntington (2020)	OECD	1978 - 2016	Long run	-0.740
Liddle and Huntington (2020)	Non-OECD	1978 - 2016	Long run	-0.250
Lin and Zeng (2013)	China	1997 - 2008	Medium run	-6.959
McRae (1994)	South Korea	1973 - 1987	Short run	-0.500
McRae (1994)	India	1973 - 1987	Short run	-0.320
Pock (2007)	EU(14)	1990 - 2004	Long run	-0.400
Pock (2007)	EU(14)	1990 - 2004	Short run	-0.171
Ramanathan (1999)	India	1972 - 1994	Short run	-0.210
Rogat and Sterner (1998)	LATAM	1960 - 1994	Long run	-0.500
Rogat and Sterner (1998)	Peru	1960 - 1994	Long run	-0.490
Rogat and Sterner (1998)	Peru	1960 - 1994	Short run	-0.200
da Silva (2009)	Brazil	2001 - 2006	Short run	-1.505
Sipes and Mendelsohr (2001)	Los Angeles	2000	Short run	-0.545

Source: Own elaboration. Literature review.

A.2 Robustness checks

Table 7: Search for simple PRC instruments: main combinations evaluated

Product	Type	Radius	Lag	Instrument	FS coef.	F	p(FS)	RF coef.	p(RF)	N
G90	dlog	1000m	lag8	zdln_prcprod_l8_1000	-0.0042***	10.85	0.002	-0.0253*	0.098	1150
G90	dlog	455m	lag7	zdln_prcprod_l7_455	-0.0073***	16.15	0.000	0.0009	0.954	1150
G90	dlog	800m	lag7	zdln_prcprod_l7_800	-0.0061***	13.76	0.001	0.0099	0.525	1150
G90	dlog	800m	lag10	zdln_prcprod_l10_800	0.0016***	12.34	0.001	0.0020	0.661	1150
G90	log	1000m	lag1	zln_prcprod_l1_1000	0.0026***	12.31	0.001	0.0166	0.294	1150
G90	level	1000m	lag1	z_prcprod_l1_1000	0.0000***	12.25	0.001	0.0002	0.279	1150
G90	dlog	455m	lag10	zdln_prcprod_l10_455	0.0016***	11.71	0.001	0.0043	0.360	1150
G90	dlog	1000m	lag10	zdln_prcprod_l10_1000	0.0012***	10.78	0.002	0.0009	0.789	1150
G90	dlog	800m	lag8	zdln_prcprod_l8_800	-0.0050***	9.98	0.003	-0.0342*	0.083	1150
G90	dlog	1000m	lag7	zdln_prcprod_l7_1000	-0.0041***	9.72	0.003	0.0095	0.415	1150
G90	dlog	800m	lag9	zdln_prcprod_l9_800	-0.0035**	5.63	0.022	-0.0347	0.133	1150
G95	dlog	800m	lag1	zdln_prcprod_l1_800	0.0020	0.40	0.531	-0.0727**	0.013	1163
G95	dlog	1000m	lag1	zdln_prcprod_l1_1000	0.0010	0.25	0.621	-0.0569**	0.010	1163
G95	dlog	455m	lag1	zdln_prcprod_l1_455	0.0020	0.16	0.689	-0.0583**	0.045	1163
G95	dlog	455m	lag2	zdln_prcprod_l2_455	-0.0004	0.01	0.925	-0.0478*	0.099	1163
G95	dlog	800m	lag2	zdln_prcprod_l2_800	-0.0002	0.01	0.941	-0.0435*	0.096	1163

Note: The table summarizes a selection of combinations evaluated for instruments based on Osinergmin reference prices. It includes useful candidates, instruments with the strongest first stage, and those with the most negative reduced form. FS refers to the first stage and RF to the reduced form. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Search for shift-share PRC instruments: main combinations evaluated

Product	Type	Radius	Lag	Instrument	FS coef.	F	p(FS)	RF coef.	p(RF)	N
G90	dlog	1000m	lag8	z_bartik_dprc_l8_1000	-0.0042***	10.92	0.002	-0.0250*	0.098	1150
G90	dlog	800m	lag8	z_bartik_dprc_l8_800	-0.0050***	10.23	0.002	-0.0338*	0.082	1150
G90	dlog	455m	lag7	z_bartik_dprc_l7_455	-0.0075***	14.90	0.000	0.0044	0.779	1150
G90	dlog	800m	lag10	z_bartik_dprc_l10_800	0.0017***	12.26	0.001	0.0023	0.614	1150
G90	dlog	800m	lag7	z_bartik_dprc_l7_800	-0.0060***	12.04	0.001	0.0122	0.421	1150
G90	log	1000m	lag1	z_bartik_lnprc_l1_1000	0.0025***	11.84	0.001	0.0167	0.285	1150
G90	dlog	455m	lag10	z_bartik_dprc_l10_455	0.0017***	11.30	0.002	0.0046	0.329	1150
G90	dlog	1000m	lag10	z_bartik_dprc_l10_1000	0.0013***	10.73	0.002	0.0012	0.739	1150
G90	dlog	455m	lag4	z_bartik_dprc_l4_455	0.0052***	9.00	0.004	0.0207	0.189	1150
G90	dlog	1000m	lag7	z_bartik_dprc_l7_1000	-0.0039***	8.00	0.007	0.0109	0.338	1150
G95	dlog	800m	lag9	z_bartik_dprc_l9_800	-0.0027	1.12	0.296	-0.0365*	0.083	1150
G95	dlog	800m	lag1	z_bartik_dprc_l1_800	0.0019	0.31	0.578	-0.0732**	0.018	1150
G95	dlog	1000m	lag2	z_bartik_dprc_l2_1000	-0.0010	0.26	0.612	-0.0349*	0.086	1150
G95	dlog	1000m	lag1	z_bartik_dprc_l1_1000	0.0009	0.17	0.685	-0.0563**	0.015	1150
G95	dlog	455m	lag1	z_bartik_dprc_l1_455	0.0019	0.13	0.718	-0.0615*	0.054	1150
G95	dlog	800m	lag2	z_bartik_dprc_l2_800	-0.0006	0.04	0.836	-0.0474*	0.079	1150
G95	dlog	455m	lag2	z_bartik_dprc_l2_455	-0.0004	0.01	0.934	-0.0477	0.101	1150

Note: The table summarizes a selection of combinations evaluated for the shift-share exposure instrument constructed using G90 and G95 reference prices, initial district-level shares, and spatial competition. FS refers to the first stage and RF to the reduced form. The presence of a relevant first stage does not necessarily imply an economically interpretable IV elasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Temporal robustness: log-log specification with fixed effects

	G90 Full	G90 Excl. 2020m3–m6	G90 2021–2022	G90 2022	G95 Full	G95 Excl. 2020m3–m6	G95 2021–2022	G95 2022
ln(*Real price*)	-1.498**	-1.679***	-2.465***	-3.383***	-2.199***	-2.468***	-3.175***	-3.296***
	(0.639)	(0.495)	(0.841)	(0.672)	(0.455)	(0.546)	(0.631)	(0.914)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1629	1438	1150	575	1641	1451	1163	582

Note: The dependent variable is $\ln Q$. Standard errors, clustered at the district level, are reported in parentheses. Singleton observations are excluded, and the degrees-of-freedom adjustment follows the baseline specification. The time windows allow the sensitivity of the estimates to the exceptional COVID-19 period to be assessed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Specification robustness: alternative transformations, 2021–2022

	G90 Log-log	G90 Level-log	G90 Log-level	G90 Asinh-log	G95 Log-log	G95 Level-log	G95 Log-level	G95 Asinh-log
Price coefficient	-2.465***	-8142.829***	-0.164***	-2.465***	-3.175***	-14419.358***	-0.158***	-3.175***
	(0.841)	(2656.758)	(0.060)	(0.841)	(0.631)	(4300.535)	(0.030)	(0.631)
Price variable	$\ln P$	$\ln P$	P	$\ln P$	$\ln P$	$\ln P$	P	$\ln P$
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1150	1150	1150	1150	1163	1163	1163	1163

Note: The table evaluates the sensitivity of the results to alternative transformations of price and quantity for the 2021–2022 period. Within each product, all specifications use the same estimation sample as the baseline log-log model. Singleton observations are excluded, and the degrees-of-freedom adjustment follows the baseline specification. Let β denote the reported price coefficient. In the log-log model, β measures the conditional percentage change in quantity associated with a 1% increase in price. In the level-log model, a 1% increase in price is associated with an approximate change of $\beta/100$ units in quantity. In the log-level model, a one-unit increase in real price is associated with an approximate percentage change in quantity of 100β; the exact percentage change is $100[\exp(\beta) - 1]$. The asinh transformation approximates the logarithm up to an additive constant for large positive quantities. These estimates describe conditional associations rather than identified causal effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.